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A review of the literature was made of the various procedures for sequencing instructional units in individualized instruction programs. Procedures for validating sequences of instructional units, or learning hierarchies, were found to fall into two general categories. One category included procedures based on coefficients of dependence, while the other category contained procedures based on more complete descriptions of the relationships between units of instruction, usually a mathematical model. Procedures based on coefficients were found to provide insufficient information for optimal sequencing of units. Procedures based on mathematical models were also found to be inadequate, but the model-based approach was found to have potential for dealing with the problem of sequencing. Recommended future research emphasizes improving model-based procedures so that they provide more information useful for determining the optimal order of instructional units. (Author/PN)

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The Validation of Learning Hierarchies

Mark D. Reckase
and
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A review was made of the various procedures for sequencing instructional units in individualized instruction programs and recommendations were made concerning the direction future research should follow. Procedures for sequencing units of instruction were found to fall into two general categories. One category included procedures based on coefficients of dependence, while the other category contained procedures based on more complete descriptions of the relationships between units of instruction, usually a mathematical model. Procedures based on coefficients were

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found to provide insufficient information for optimal sequencing of units. Procedures based on mathematical models were also found to be inadequate, but the model-based approach was found to have potential for dealing with the problem of sequencing. Recommended future research emphasizes improving model-based procedures so that they provide more information useful for determining the optimal order of instructional units.

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The Validation of Learning Hierarchies

One of the most rapidly growing areas in the field of education today is the area of individualized instruction--instruction in which content, organization, or pacing is modified for each individual. Programs of individualized instruction have been implemented in such areas as electronics (Peiper, Swegey, and Valverde, 1970), engineering (Schure, 1965), mathematics (Bushnell, 1966), psychology (Kulik, 1972), and vocational and technical education in the military (Impelliterri and Finch, 1971). These programs employ several different types of educational technology, including personalized systems of instruction (PSI), computer-assisted instruction (CAI), individually prescribed instruction (IPI), and programmed instruction (PI).

Although individualized instruction comes in many forms, all of these forms share the same basic design. All are essentially sequences of instructional units through which subjects are routed by means of a series of tests. The way in which these units are sequenced is one of the more crucial components of any individualized instruction program. The units should be arranged in such a fashion that prerequisite material is covered first, followed by more advanced material. How this ordering is determined has been the topic of considerable research. The purpose of this report is to evaluate the various approaches to sequencing instructional units that have been reported in the literature, and to make recommendations on the direction future research should follow.

Most of the procedures that have been proposed for sequencing instructional units have been based on the work of Gagné (1962), and have involved the use of various techniques for validating learning hierarchies constructed using his task analysis methodology. Procedures for validating hierarchies have generally taken one of two approaches. One approach has been to simply compute a coefficient that measures the strength of the hierarchical relationships, and on the basis of the coefficient accept or reject the hierarchy. The other approach has been to more completely describe the relationships among the instructional units, usually by means of a mathematical model, and to decide on the basis of the description whether the relationships are of the desired nature. Both approaches will be discussed, as will be a number of examples of each approach. First, however, a discussion of Gagné's work on learning hierarchies will be presented.

The Work of Gagné

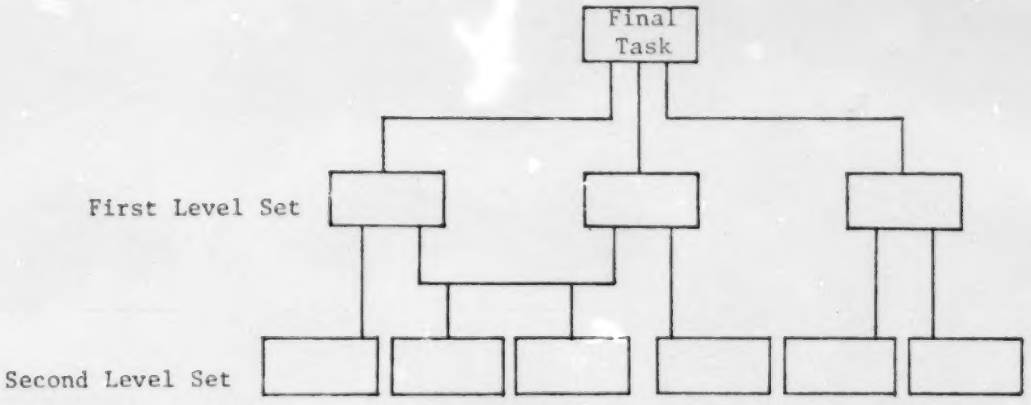
In a series of articles dating from 1961, Gagné and his coworkers investigated the learning of mathematical skills. A hypothesis originating from this research was that a class of tasks necessary to attain a learning outcome could be sorted into a hierarchy of sets of tasks, each set being a group of tasks at the same level in the hierarchy. The structure of the hierarchy would be such that there could be positive transfer of learning from one learning set to a higher level learning set until the final learning outcome was achieved. Gagné (1962) proposed that one could establish a learning hierarchy by determining the skills an individual would have to possess in order to attain the learning outcome. One would then make the same determination for each of those skills. This process would be continued

until one developed a hierarchy containing the most basic skills as the learning set at the lowest level. If the established hierarchy were correct, then, positive transfer from each lower learning set to the next higher learning set would be promoted (Gagné, 1962).

The successful establishment of a learning hierarchy results in a vertical structure of learning sets, with any high level learning set having one or more immediately prerequisite learning sets. Figure 1 presents an example of a derived learning hierarchy. In this hierarchy, the terminal task has three prerequisite tasks, which in turn have six second level prerequisite tasks. Mastery of the lower tasks is required before a final task can be performed.

Figure 1

An Example of a Derived Hierarchy



Gagné (1968) identified two characteristics necessary for the successful establishment of a learning hierarchy. One such characteristic is that of sequencing: a learner who is able to perform successfully a higher level set of tasks should also be able to perform all lower level sets of tasks in the hierarchy. The other characteristic is transfer: attainment of a lower level learning outcome should increase the probability of successful attainment of a higher level learning set. The existence of these two characteristics establishes that there is an ordered relationship among the learning sets within the hierarchy. If a learning hierarchy has been successfully established, it should be possible to validate the hierarchy by demonstrating the presence of these characteristics. Most of the procedures for validating hierarchies, including Gagné's own procedure, are based on this premise. Those procedures will now be discussed.

Procedures for Validating Hierarchies

As was previously mentioned, there have been two basic approaches to validating hierarchies constructed using task analysis procedures, one based on coefficients and one based on more complete descriptions of the relationships among sets of learning tasks. These two approaches will now be discussed in more detail, and several examples of each will be presented. After the approaches and examples have been discussed, an evaluation of the approaches will be presented.

Coefficient-Based Procedures

The basic objective of the coefficient approach for validating learning hierarchies is to compute the value of a coefficient that will measure the strength of the ordered relationships among learning sets or tasks. A number of coefficients have been proposed for this purpose, most of which are variations on the proportion of positive transfer (PPT) statistic proposed by Gagné and Paradise (1961). The PPT statistic will be described first, and then the ways in which it has been modified will be discussed. Afterward, several coefficients not based on the PPT statistic will be discussed.

The PPT Statistic The PPT statistic is based on the four pass/fail combinations possible for two learning tasks. If Task 2 follows (is dependent on) Task 1 and N_{00} is the number of subjects failing on both tasks, N_{10} is the number of subjects succeeding on Task 1 but failing on Task 2, and N_{11} is the number of subjects succeeding on both tasks, then the PPT statistic is given by

$$PPT = \frac{N_{00} + N_{11}}{N_{00} + N_{10} + N_{11}} .$$

This statistic is used to measure the level of positive transfer from Task 1 to Task 2. If the level of positive transfer is high, then fewer subjects will succeed on Task 1 without succeeding on Task 2 than would have if the level of transfer had been low. Thus, the greater the positive transfer, the smaller is N_{10}. As N_{10} decreases, the PPT statistic increases. When N_{10} is 0, the PPT statistic has a value of 1.0, which is the maximum value it can take on.

The PPT statistic appears to be a reasonable indicant of the level of positive transfer between two tasks. However, positive transfer does not necessarily indicate that there is a hierarchical relationship between the two tasks. It is possible that the positive transfer from Task 2 to Task 1 is as great as the positive transfer from Task 1 to Task 2. The PPT statistic does not indicate the direction of the positive transfer. In fact, if the tasks are reversed so that Task 2 becomes the first task and Task 1 becomes the second task, an equal or higher value may be obtained for the PPT statistic as was obtained before the reversal, but in this situation the statistic indicates positive transfer from the subsequent task to the precedent task. Because of this limitation on the interpretation of the PPT statistic, a number of alternative statistics, most of which are variations of the PPT statistic, have been proposed.

Variations on the PPT Statistic The Commission on Science Education of the American Association for the Advancement of Science (Walbesser, 1968) proposed a procedure for validating hierarchies that employs three statistics rather than one. These three statistics are the consistency, the adequacy, and the completeness ratios. These ratios use the same four pass/fail combinations that were used for the PPT statistic.

The consistency ratio (CR) is given by

$$CR = \frac{N_{11}}{N_{11} + N_{10}},$$

where the terms are as defined for the PPT statistic. As can be seen, the CR statistic is the same as the PPT statistic, except that the N_{00} term is omitted. The N_{00} term is omitted because, while it is consistent with the hypothesized hierarchical relationship, it is not an indication of positive transfer (Walbesser and Eisenberg, 1972).

Consistency is a necessary but not sufficient condition for a valid hierarchy, according to Walbesser (1968). In addition, adequacy and completeness must be considered. Adequacy refers to how often the learner has achieved a behavior after the relevant subordinate behavior has been attained. The adequacy of a hierarchy is measured using the adequacy ratio (AR), which is given by

$$AR = \frac{N_{11}}{N_{11} + N_{01}}.$$

Completeness is an indication of the number of examinees that have reached the terminal behavior relative to those that have made no progress. High consistency and adequacy ratios are misleading if only small numbers of examinees acquire the terminal behavior and at least some subordinate behaviors. Thus, a large value for N_{00} would be evidence of incomplete instruction. The completeness ratio (COR) is given by

$$COR = \frac{N_{11}}{N_{11} + N_{00}}.$$

A procedure for validating hierarchies proposed by Walbesser and Eisenberg (1971) employs the consistency, adequacy, and completeness ratios, and in addition uses two other coefficients. These coefficients are the inverse consistency ratio (ICR) and the inverse adequacy ratio (IAR). While consistency indicates that the acquisition of the terminal behavior implies the acquisition of subordinate behaviors, the inverse consistency ratio measures the extent to which nonacquisition of the terminal behavior implies nonacquisition of subordinate behaviors. The inverse consistency ratio is given by

$$ICR = \frac{N_{00}}{N_{00} + N_{01}}.$$

The adequacy ratio measures the extent to which the acquisition of all subordinate behaviors implies acquisition of the terminal behavior, while the inverse adequacy ratio indicates the degree to which nonacquisition of the subordinate behavior implies nonacquisition of the terminal behavior. The inverse adequacy ratio is given by

$$IAR = \frac{N_{00}}{N_{00} + N_{10}}.$$

Non-PPT Based Statistics Not all of the coefficients that have been proposed for validating hierarchies have been variations on the PPT statistic. For instance, Capie and Jones (1971) used the phi coefficient for validating hierarchies. The phi coefficient is based on the same four pass/fail combinations that were used for the PPT-like statistics. However, rather than computing a ratio of the numbers of subjects in specified groups, a product moment correlation coefficient is computed.

The Guttman coefficient of reproducibility has also been used to validate hierarchies (Hofman, 1977; Resnick and Wang, 1969). An assumption made when this statistic is used is that the learning tasks are ordered according to their difficulty. If an individual gives five correct responses on 10 items, it is assumed that the individual responded correctly to the five easiest items. This statistic, then, is a measure of the relationship between the response pattern of an individual and the number of correct responses by that individual. If the response pattern is not accurately predicted by the number of correct responses, a perfect Guttman scale is not present. The proportion of responses that follow the predicted pattern is called the coefficient of reproducibility. To the extent that some respondents achieve success on some of the more difficult tasks but fail on less difficult tasks, the coefficient of reproducibility is reduced in magnitude. For a pair of tasks in a hierarchy, the extent to which some respondents achieve success on the superordinate task but fail the subordinate task, the coefficient is reduced. The coefficient of reproducibility for the hierarchy is the average coefficient of reproducibility for all of the pairs of superordinate and subordinate tasks in the hierarchy (Hofman, 1977).

Another statistic that has been used for validating hierarchies is the proportion of disconfirmatory response patterns (Airasian and Bart, 1975). This procedure is based on ordering theory, which provides a basis for determining logical relationships among tasks (Bart and Krus, 1973). If it is assumed that Task 1 is prerequisite to Task 2, then the response pattern (0,1), which indicates success on Task 2 but failure on Task 1, is considered disconfirmatory. The response patterns (0,0), (1,0), and (1,1) are considered to be confirmatory. The proportion of disconfirmatory response patterns (PD) is given by

$$PD = \frac{N_{01}}{N_{00} + N_{10} + N_{01} + N_{11}}.$$

One other statistic that has been used for validating hierarchies is the conditional item difficulty index (Airasian, 1971). The conditional difficulty of an item is computed using only the subjects having response patterns that are predicted from the hierarchy. For instance, for a three-task hierarchy the only response patterns expected are:

(a) 000,
(b) 100,
(c) 110,
and (d) 111,

even though there are eight patterns possible. If n_0, n_1, n_2, and n_3 are the number of subjects with response patterns (a), (b), (c), and (d) above, respectively, then only $n_0 + n_1 + n_2 + n_3$ subjects will be considered when computing a conditional item difficulty. The conditional difficulty for an item is given by the number of subjects having expected response patterns in which the item was correctly answered, divided by the number of subjects having expected response patterns in which all preceding items are correct. Thus for the first task in the three-task hierarchy the conditional difficulty (CD) is given by

$$CD = \frac{n_1 + n_2 + n_3}{n_0 + n_1 + n_2 + n_3}.$$

For the second task the conditional difficulty is given by

$$CD = \frac{n_2 + n_3}{n_1 + n_2 + n_3},$$

and for the third task the conditional difficulty is given by

$$CD = \frac{n_3}{n_2 + n_3}.$$

The conditional item difficulty indices computed for a set of tasks help to determine the validity of a hierarchy by indicating the extent to which failure on earlier tasks is predictive of failure on later tasks. For example, if the conditional difficulty of an item is very low given that all preceding items have been correctly answered, the completeness of the sequence is questionable (Airasian, 1971).

Summary of Coefficient Procedures The basic objective of the coefficient approach to validating hierarchies is to compute a coefficient that will indicate the strength of the hierarchical relationships among learning tasks. Many different coefficients have been proposed for this purpose, including: the proportion of positive transfer statistic; the consistency, adequacy, completeness, inverse consistency, and inverse adequacy ratios; the Guttman coefficient of reproducibility; the phi coefficient; the proportion of disconfirmatory response patterns; and the conditional item difficulty index. Table 1 summarizes the coefficients that have been discussed.

One reason why so many coefficients have been proposed is that each coefficient tends to be associated with only one aspect of the complex relationship between tasks in a hierarchy. This has led some researchers to propose the use of multiple coefficients for the validation of hierarchies (Walbesser, 1968; Walbesser and Eisenberg, 1972). Other researchers have proposed that more complete descriptions of the relationship between learning tasks is needed than can be provided by coefficients alone. These researchers have tended to use mathematical models to describe the relationships among learning tasks. This approach to validating learning hierarchies will be discussed next.

Model-Based Procedures

Model-based procedures specify a mathematical model to describe the relationship between performances on different tasks in a hierarchy. This is commonly done using a mathematical expression describing the probability of success on a task given the performance (acquisition vs. nonacquisition) on lower level tasks. The adequacy of the model for describing the relationship between performances on different tasks can be tested statistically. If the performance on a task predicted from the model does not differ significantly from observed data, then the data support the hypothesized structure of the hierarchy and the form of the mathematical model. If the model does not fit the data, the failure may be due to errors in the hypothesized structure of the hierarchy, errors in the form of the mathematical model, or both.

Proctor Model One of the first mathematical models proposed for validating learning hierarchies was described by Proctor (1970). This model is a probabilistic formulation of Guttman scaling. The items in the proposed hierarchy are assumed to form a Guttman scale. Each response pattern consistent with the Guttman scale is associated with a true ability level. It is assumed that patterns that are inconsistent with the scale are also associated with one of the true ability levels, but that they contain error. The probability that an observed response pattern is associated with a given true ability level is the probability of finding an examinee with that true ability level multiplied by the probability that an examinee with that ability level would give the observed response pattern. This second probability decreases as the difference between the observed pattern and the pure pattern associated with that level of ability increases. The probability of the occurrence of an observed response pattern is the sum of the probabilities of the pattern over each of the true ability levels.

As an example, suppose that every subject in a population belongs to one of the several ability levels, each of which has associated with it a true Guttman type response pattern. For a three item scale there are four true Guttman patterns--(000), (100), (110), and (111). Every subject, then, belongs to one of the four ability levels associated with these patterns. The probability of an observed response pattern for this scale is the sum of four terms--the probability of finding a subject whose true ability level was associated with the (000) pattern and who responded with the observed pattern, the probability of finding a subject who should have responded with the (100) pattern but who responded with the observed pattern, and so on until all four true patterns have been considered. In its mathematical form, the probability of the observed pattern for the three item scale is given by

$$P(\underline{x}) = \alpha^{n_1}(1-\alpha)^{4-n_1}\theta_1 + \alpha^{n_2}(1-\alpha)^{4-n_2}\theta_2 + \alpha^{n_3}(1-\alpha)^{4-n_3}\theta_3 + \alpha^{n_4}(1-\alpha)^{4-n_4}\theta_4 \quad , \qquad (1)$$

where $\underline{x}$ is the observed pattern; θ_1, θ_2, θ_3, and θ_4 are the proportions of the population having each true ability level; the α term is the probability of a subject responding to an item in a way inconsistent with the true pattern associated with the subject's true ability; and the n_1, n_2, n_3, and n_4 terms are the number of items in the observed pattern inconsistent with the true pattern for each of the four ability levels.

Table 1

A Summary of the Coefficient Procedures
for the Validation of Learning Hierarchies

Procedure	Proponent
Proportion of Positive Transfer	Gagné and Paradise (1961)
PPT Based Statistics	
Consistency Ratio	Walbesser (1968)
Adequacy Ratio	
Completeness Ratio	
Inverse Consistency Ratio	Walbesser and Eisenberg (1971)
Inverse Adequacy Ratio	
Non-PPT Based Statistics	
Phi Coefficient	Capie and Jones (1971)
Coefficient of Reproducibility	Hofman (1977), Resnick and Wang (1964)
Proportion of Disconfirmatory Response Patterns	Airasian and Bart (1975), Bart and Krus (1973)
Conditional Item Difficulty	Airasian (1971)

To apply this model, it is assumed that the frequencies of the observed response patterns are distributed multinomially with probabilities given by the model. A test of the fit of the multinomial model (with the probabilities from the model as parameters) to the observed frequencies can be performed.

White and Clark Model A somewhat different model was introduced by White and Clark (1973). This model tests the hypothesis that all subjects who possess a certain skill form a subset of the group of subjects who possess a second skill. This model is called the C statistic model.

In using this model, a matrix of response frequencies is developed using the format shown in Table 2. The population subgroups are defined as follows:

P_O = proportion of the population having neither skill,

P_B = proportion of the population having both skills,

P_I = proportion of the population having only Skill I, and

P_{II} = proportion of the population having only Skill II.

Table 2

Response Frequency Matrix for White and Clark Model

Number of Lower Skill Questions Correctly Answered	Number of Higher Skill Questions Correctly Answered 0	1	2	TOTAL
2	P_{20}	P_{21}	P_{22}	n_{12}
1	P_{10}	P_{11}	P_{12}	n_{11}
0	P_{00}	P_{01}	P_{02}	n_{10}
TOTAL	n_{20}	n_{21}	n_{22}	N

Note: N is the total number of subjects in the sample, while n_{ij} is the number of subjects correctly answering j items for skill i.

The conditional probabilities of group members having answered the appropriate number of items correctly are:

θ_a = probability of examinee with Skill I answering correctly any item for Skill I,

θ_b = probability of examinee without Skill I answering correctly any item for Skill I,

θ_c = probability of examinee with Skill II answering correctly any item for Skill II, and

θ_d = probability of examinee without Skill II answering correctly any item for Skill II.

The total probability of a cell is thus defined as the product of the probability of the examinee being in a group and the conditional probability of members of that group answering the appropriate number of items correctly. If the various P's and θ's are known, a probability estimate for each cell in Table 2 can be calculated. Estimates of the P's and θ's can be calculated using the cell frequencies or the marginal totals using a maximum likelihood procedure (see White and Clark, 1973). In a two-item case, P_{02} can be derived by substituting the estimates of P and θ in the equation:

$$P_{02} = P_0(1-\theta_b)^2\theta_d^2 + P_I(1-\theta_a)^2\theta_d^2 + P_{II}(1-\theta_b)^2\theta_c^2 + P_B(1-\theta_a)^2\theta_c^2 \quad . \qquad (2)$$

Once the probabilities of all the cells have been computed, the probability of the observed distribution under H_0 can be calculated using the observed cell frequencies and estimated probabilities as parameters of the multinomial distribution. A test of significance can be performed by summing the

probabilities of all possible distributions which show a deviation from the hypothesis as great or greater than that of the observed distribution (White and Clark, 1973). In order to reduce the amount of computation required, White and Clark (1973) suggest forming the test using only the (0,2) cell. The observed frequency and estimated probability for this cell could be used as parameters for the binomial distribution, and H_0 would be rejected whenever the observed frequency exceeded a critical value of C. The value of C, of course, depends on the desired error rate, the sample size, and the magnitude of the probability estimated for the (0,2) cell.

Dayton and Macready Model A third mathematical model for the validation of learning hierarchies was proposed by Dayton and Macready (1976). This model is essentially a generalization of the Proctor model, and also subsumes the White and Clark model (Dayton and Macready, 1976).

For any K dichotomously scored tasks, the scores on those tasks may be summarized by a column vector, U, composed of 0's and 1's. A score of 0 may arise from an incorrect response or from an omission. The product $S = U' U$ is the number of items or tasks successfully completed by a respondent. Assume there exists an a priori hierarchy, and there exists a set of q distinct pattern vectors, V_j, comprised of 0's and 2's, which for the hypothesized hierarchy defines acceptable response patterns. (The values 0 and 2 are used instead of 0 and 1 so that the vector difference V - U will provide information necessary to compute the values of the exponents in the model.) For example, when K = 4, a linear hierarchy would be represented by q = 5 pattern vectors:

$$V_1 = (0000),$$

$$V_2 = (2000),$$

$$V_3 = (2200),$$

$$V_4 = (2220),$$

$$V_5 = (2222).$$

In the most general form the probabilistic model may be written as:

$$P(\underline{u}) = \sum_{j=1}^{q} \left\{ \left(\prod_{i=1}^{K} \alpha_i^{a_{ij}} (1 - \alpha_i)^{b_{ij}} \beta_i^{c_{ij}} (1 - \beta_i)^{d_{ij}} \right) \cdot \theta_j \right\}, \quad (3)$$

where a_{ij}, b_{ij}, c_{ij}, and d_{ij} are defined as follows. Let g_{ij} be the ith element in $V_j - U$. Then,

$$a_{ij} = \begin{cases} 1 & \text{if } g_{ij} = -1 \\ 0 & \end{cases},$$

$$b_{ij} = \begin{cases} 1 & \text{if } g_{ij} = 0 \\ 0 & \end{cases},$$

$$c_{ij} = \begin{cases} 1 & \text{if } g_{ij} = 2 \\ 0 & \text{otherwise} \end{cases},$$

$$d_{ij} = \begin{cases} 1 & \text{if } g_{ij} = 1 \\ 0 & \text{otherwise} \end{cases}.$$

The parameter θ_j represents the probability that the jth pattern vector occurs. It is the hypothetical population proportion of respondents that achieves Level j of the hierarchy. The parameter α_i represents the probability that a respondent produces a correct response to a task, which relative to a specific pattern vector should not have been correctly completed. The α_i parameter is referred to as the guessing parameter. The parameter β_i is the probability that a respondent produces a response that is incorrect which should have been completed correctly relative to a specific pattern vector. The parameter β_i is the forgetting parameter. For this model, the occurrence of guessing and forgetting are assumed to be independent across items (Dayton and Macready, 1976).

A restriction on θ_j is

$$\sum_{j=1}^{q} \theta_j = 1. \qquad (4)$$

Also, the parameters (θ_j, α_i, β_i) are meaningful only over the interval 0 to 1 (Dayton and Macready, 1976).

For any given task, three of the four variables a_{ij}, b_{ij}, c_{ij}, and d_{ij} will be equal to 0, and one of the four will take on the value of 1. This model allows for $2^n - 1$ independent parameters, where n is the number of items. Once the parameters have been estimated, the Pearson chi-square or likelihood ratio chi-square test may be used to provide a goodness-of-fit test (Dayton and Macready, 1976).

Loglinear Models Another class of models have been described by Goodman (1975) and Davison (1981). These models are based on an application of loglinear analysis to the problem of discovering or confirming learning hierarchies. Loglinear analysis utilizes data in the form of a contingency table, but is not limited to dichotomous variables, nor to pairwise comparisons (Davison, 1981). For a discussion of loglinear models, see Bishop, Feinberg and Holland (1975).

For simplicity, the presentation of the model described by Goodman (1975) will be limited to the case of three variables, each having three response categories. The variables used could be items (for which the response categories would be item responses), or tests (for which the response categories would be test score categories). The three variables and their response categories form a contingency table, in this case, a three-way contingency table. Cell entries represent frequencies of subjects exhibiting the response vector represented by each cell. That is, the entry in cell (a, b, c) would be the number of subjects responding a to the first variable, b to the second, and c to the third.

Given an a priori or hypothesized sequence among the three variables, the contingency table can be broken down into two classes of cells: those cells representing response vectors compatible with the hypothesized sequence, and those cells representing the vectors inconsistent with the hypothesized sequence. Subjects are divided into k + 1 classes, where k is the number of cells representing response vectors compatible with the hypothesized sequence. The (k + 1)th class is the group of subjects exhibiting incompatible response vectors. The proportion of subjects in each class is represented by P_i (i = 0, 1, . . ., k), where P_0 is the proportion in the class having inadmissible responses.

Within the class of inadmissible cells, which is called the unscaleable class, the variables are assumed to be independent, so that the probability of observing any given response vector is simply the product of the probabilities of each of the responses to the three variables. That is, P(a,b,c,) = P(a)P(b)P(c) for any unscaleable subject. Therefore, the joint probability of a randomly selected subject being in the unscaleable class and having response vector (a, b, c) is $P_0P(a)P(b)P(c)$, regardless of whether cell (a, b, c) is admissable or inadmissable. The probability of a subject from the scaleable class being in an inadmissible cell is zero. If (a, b, c) is an admissible response vector, the probability of a scaleable subject having that response vector is P_k, if (a, b, c) is the kth admissible cell. Of course, the probability of a subject from the kth class having a response vector represented by the jth cell, where $j \neq k$, is zero. This leads to the following equation, which is fundamental to the model:

$$P(a, b, c) = \begin{cases} 0 + P_0P(a)P(b)P(c) \text{ if } (a, b, c) \text{ is inadmissible} \\ P_k + P_0P(a)P(b)P(c) \text{ if } (a, b, c) \text{ is admissible.} \end{cases}$$

This model is fitted to the data by one of several proposed algorithms (Goodman, 1975; Davison, 1980; Bishop, Fienberg and Hollard, 1975; Fienberg 1977), and Pearson chi-square and likelihood ratio chi-square fit statistics can be obtained.

Summary of Model-Based Procedures A number of mathematical models for use in validating learning hierarchies have been presented. These procedures are summarized in Table 3. Although there are four procedures listed in Table 3, those four procedures actually represent only two distinct types. One type is represented by the Dayton and Macready procedure, which subsumes the Proctor model and the White and Clark model. The other type of procedure is represented by the Goodman and Davison model.

Table 3

A Summary of the Procedures for the Validation of Learning Hierarchies Based on Mathematical Models

Procedure	Proponent
Guttman Model	Proctor (1970)
C Statistic Model	White and Clark (1973)
General Probabilistic Model	Dayton and Macready (1976)
Loglinear Model	Goodman (1975), Davison (1981)

Evaluation of Procedures for Validating Hierarchies

The process of establishing a valid hierarchy involves much more than the application of models and statistics to the response patterns of individuals or the mere application of Gagné's task analysis procedure. Before evaluating the procedures that have been proposed for the validation of learning hierarchies, a program in which the procedures should be applied will be discussed. Afterward, the criteria to be used to evaluate the procedures within this context will be presented, followed by an evaluation of the procedures.

A Program for Constructing and Validating Hierarchies White (1974a) has proposed a nine stage program for the construction and validation of learning hierarchies that is comprehensive and directed at solving some of the problems encountered in the construction of learning hierarchies. The nine stages in the program are:

(a) Define in behavioral terms the element that is to be the highest stage of the hierarchy;
(b) Derive the hierarchy by applying Gagné's task analysis procedure;
(c) Check the reasonableness of the postulated hierarchy with experienced teachers and subject matter experts;
(d) Invent possible divisions of the elements of the hierarchy, so that very precise definitions are obtained;
(e) Carry out an investigation of whether the invented divisions do in fact represent different skills;

(f) Write a learning program for each element, and embed in it mastery tests for each element;
(g) Have at least 150 suitably chosen subjects work through the program, taking the tests as they come to them;
(h) Analyze the results to see whether any of the postulated connections between elements should be rejected; and
(i) Remove all rejected connections from the hierarchy.

Cotton, Gallagher, and Marshall (1977) have proposed a tenth stage which is to be used only if 15% or more of the connections were rejected. This stage would involve repeating stages (f) through (i), using the revised hierarchy with a different group of subjects.

The procedures that have been proposed for validating hierarchies are not employed until stage (h) of the White model. At this stage of the process a hierarchy has been postulated, and its reasonableness checked by experts and experienced teachers. What is needed at stage (h) is a procedure for validating the postulated hierarchical relationships between the elements of the hierarchy. The criteria for selecting such a procedure will now be discussed.

Selection Criteria The first criterion for selecting a procedure for validating the hierarchical relationships between elements in a postulated hierarchy is that the procedure must provide information as to the direction of the relationship. Simply providing an indication of the strength of an association between elements is not sufficient. There could be a strong association between a subordinate and a superordinate element in a proposed hierarchy simply because the two elements measured the same skill. The strong association does not imply that the superordinate element could not have been attained without prior success on the subordinate element. It must be demonstrated that success on the first element is not only sufficient, but a necessary condition for success on the second element.

Another criterion is whether the procedure provides information useful for correcting the structure of the hierarchy if any connections are rejected as invalid. This includes information that would indicate whether the elements are out of order, whether any unnecessary elements are included, and whether any necessary elements were omitted from the hierarchy.

A third criterion for selecting a procedure for validating hierarchies is whether the procedure indicates how successful a subject must be on an element before success is likely on the subsequent element. When a single dichotomously scored item is used for each element, this is not an issue. But when each element involves a multi-item test, it is possible to reject a hierarchical relationship simply because success was poorly or incorrectly defined for that element.

There are undoubtedly other criteria that could be included in this list. However, these should be adequate for evaluating the overall approaches to validating learning hierarchies. A detailed comparison of individual models with an eye toward selecting one or the other might require a more complete list of selection criteria. That is not the purpose here. The purpose here is to evaluate the approaches to validating hierarchies that have been followed by researchers in order to make recommendations on the direction future research should follow.

Evaluation of the Coefficient Approach On the basis of the criteria for evaluation set out above, it must be concluded that the coefficient approach to the validation of learning hierarchies is inadequate. There are numerous problems with each of the coefficients, but a more serious problem is the basic inadequacy of the approach itself. The first criterion for evaluation was that a validation procedure must indicate direction as well as strength of a relationship. Coefficients such as those that have been proposed for validating learning hierarchies do not indicate direction. For instance, consider the case where N_{00} is 20, N_{01} is 0, N_{10} is 20, and N_{11} is 60. For this case, the PPT statistic has a value of .80, CR = .75, AR = 1.0, COR = .75, and phi = .61. If the two tasks are reversed, N_{01} is 20 and N_{10} is 0. These values yield a PPT statistic equal to 1.0, CR = 1.0, AR = .75, COR = .75, and phi = .61. Reversing the two tables did not change the values of phi and COR, and though it did change the values of the PPT and CR statistics, those statistics had high values regardless of which task was labeled Task 1. Clearly these statistics are not indicants of the direction of the relationship between the two tasks.

Coefficients such as these also do not reliably indicate when unneccessary elements are included in the hierarchy or necessary elements are omitted. If an unneccessary element is redundant, it will probably be correlated with another element or perhaps several elements in the hierarchy. Such a correlation might result in high coefficient values and acceptance of the unnecessary element. When a connection is rejected, there is no indication as to whether the connection was invalid or whether a necessary element was omitted. Task 1 might be necessary but not sufficient for attainment on Task 3. Without Task 2, even subjects successful on Task 1 might be unable to attain success on Task 3. In this case the hierarchy might be rejected without there being any indication that the hierarchy might have been acceptable had Task 2 been included. The same situation might arise if Task 2 were included, but Tasks 2 and 3 were reversed in order.

White (1974b) has listed some other inadequacies of these coefficients. These inadequacies include the following: because the sampling distributions for many of the coefficients are unknown there is no way to determine the error in estimation; and, these coefficients do not provide information useful for defining success on multi-item tests. Based on White's criticisms of the coefficient approach and those listed above, it must be concluded that the use of coefficients for validating learning hierarchies does not appear to be a productive direction for future research.

Evaluation of the Model Approach Applying the criteria for evaluation to the model-based procedures for validating hierarchies that have been proposed leads one to conclude that this is a very promising approach, but that the procedures so far developed fall short of fully exploiting their potential. The two types of models that have been proposed are a considerable improvement over the coefficient approach. When the fit of a particular model to the observed data is satisfactory, then a reasonable amount of confidence can be placed in the validity of the hierarchy. Because the mathematical model specified in the procedure describes the way in which performance on one element in a hierarchy is related to performance on another element, the direction of the relationship is indicated. Moreover, because the mathematical model is generally in the form of a probability statement conditioned on a latent variable, the results are generalizable beyond the sample used.

However, there are several problems with the models that have been proposed. One problem is that very little information is obtained for use in defining the criterion for success on multi-item tests. Another serious problem is encountered when the fit of the model to the observed data is inadequate. When the model is rejected, it is not easy to determine why it was rejected. A model could be rejected because the hierarchy is incorrectly specified, because the mathematical model is of an inappropriate form, or both. No information is provided as to whether unnecessary elements were included or necessary elements were omitted. Because of these inadequacies, the model-based procedures that have been proposed need improvement. More research on this approach is needed.

Summary and Recommendations

Summary The area of individualized instruction was identified as one of the fastest growing areas in the field of education. One of the most crucial components of individualized instruction was found to be the sequencing of instructional units. A review of the literature was undertaken to identify the major alternatives available for sequencing units of instruction in such a way as to facilitate education.

Procedures for validating sequences of instructional units, or learning hierarchies, were found to fall into two general categories. One category included procedures based on coefficients of dependence, while the other category contained procedures based on more complete descriptions of the relationships between units of instruction, usually a mathematical model. An evaluation of these two approaches to validating learning hierarchies was undertaken in order to facilitate the formulation of recommendations for the direction of future research in this area.

Procedures based on coefficients were found to provide insufficient information for the validation of hierarchies or for correcting deficiencies in the structure of a proposed hierarchy. Procedures based on mathematical models were also found to be inadequate, but the model-based approach was found to have potential for dealing with the problem of learning hierarchy validation. Recommendations for future research follow.

Recommendations In future research on the validation of learning hierarchies, emphasis should be placed on improving the currently available model-based procedures in several ways. A validation procedure should provide information useful for defining success on the elements of a learning hierarchy, as well as information as to whether important elements have been omitted, inappropriate elements have been included, or some elements have just been placed in the wrong order. Developing a procedure that will provide all this information will make it possible not just to accept or reject a hierarchy, but to correct deficiencies in the structure of rejected hierarchies. It appears that the development of such a procedure would greatly facilitate future development of the field of individualized instruction.

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